IMPROVING FORECASTS OF RUNOFF

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Generate an archive of atmospheric forecasts



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Develop downscaling relationships, and apply to the operational forecast model



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Estimate basin initial conditions



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Run hydrologic models in ensemble mode to provide probablistic forecasts of streamflow and estimates of forecast uncertainty



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□ Perform side-by-side comparisons with operational NWS forecasts, and, where appropriate, infuse our procedures in regular NWS operations

MRF FORECAST ARCHIVE

□ The NCEP/NCAR reanalysis –

a 40+ year record of global atmospheric fields and surface fluxes derived from a numerical weather prediction and data assimilation system kept unchanged over the analysis period

 Every five days, a single realization of an 8-day forecast was run

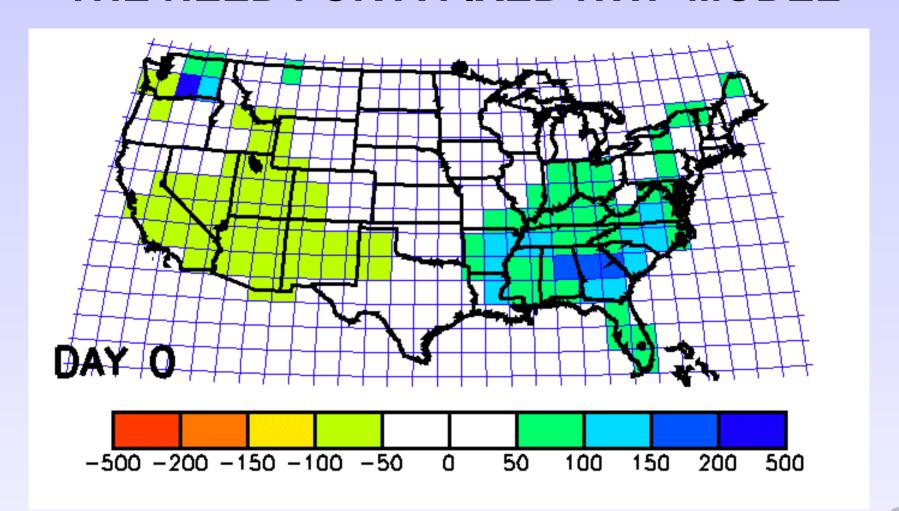
for the period 1958-1998, this provides over 2500 8-day forecasts that can be compared with observations

Model output is archived on a regular lat/lon grid with approx 1.875° horizontal resolution.

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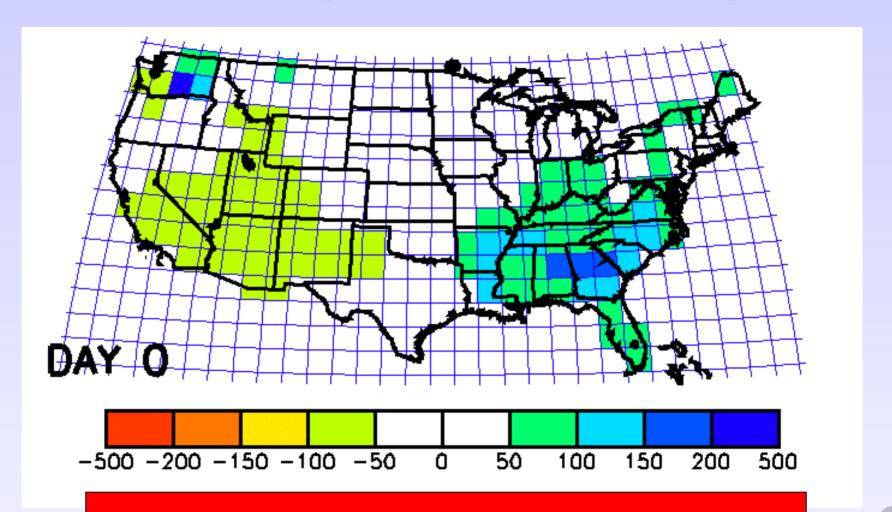


THE NEED FOR A FIXED NWP MODEL

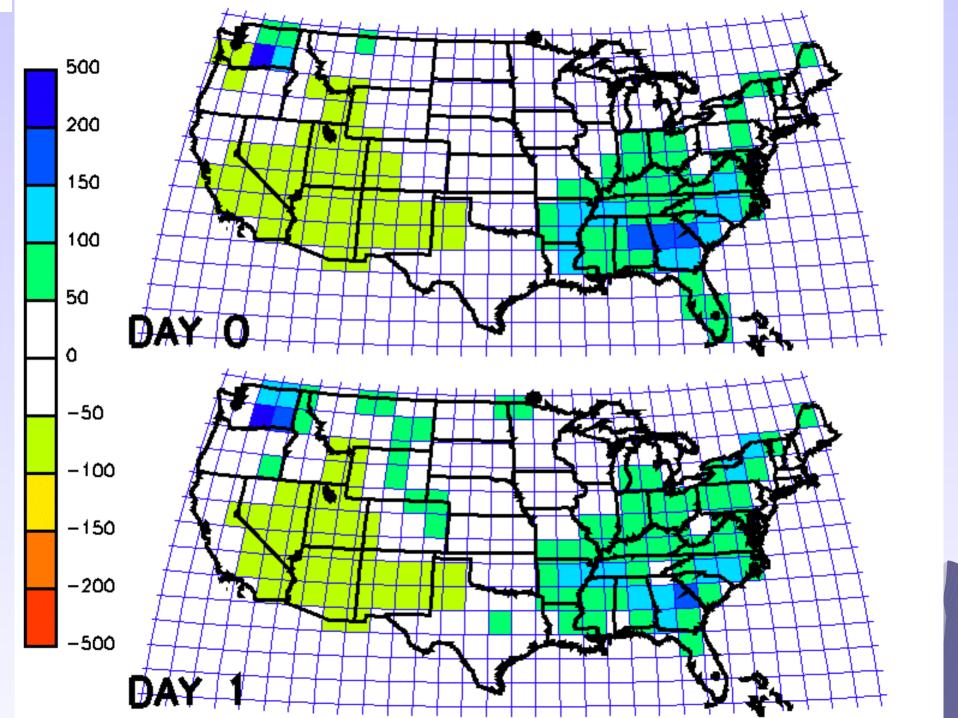


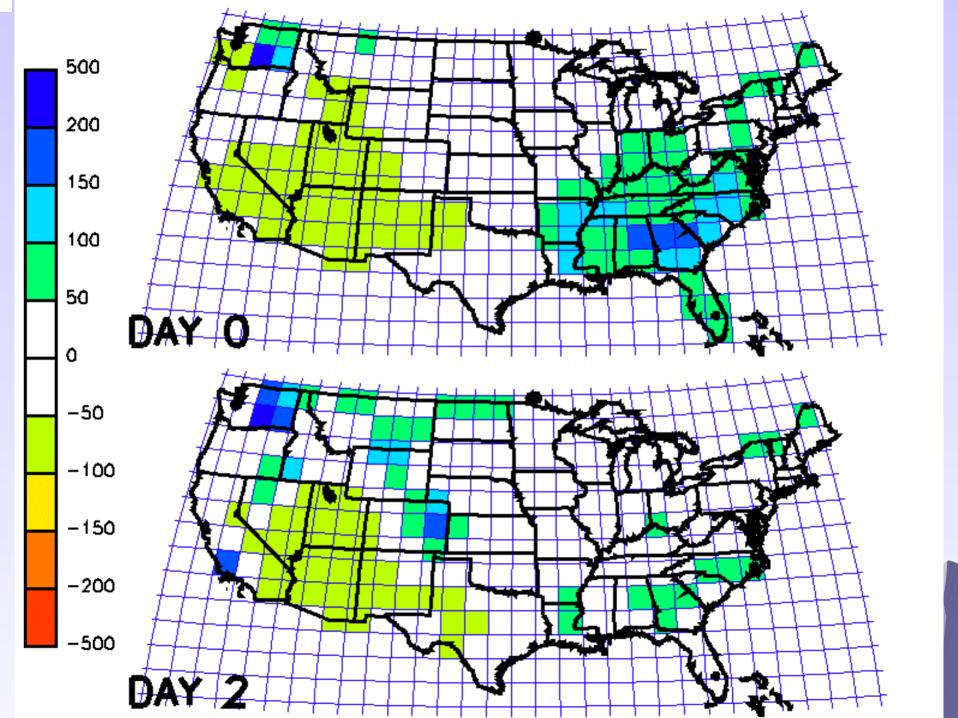
□ Model July precipitation biases (% mean) in the NCEP/NCAR reanalysis

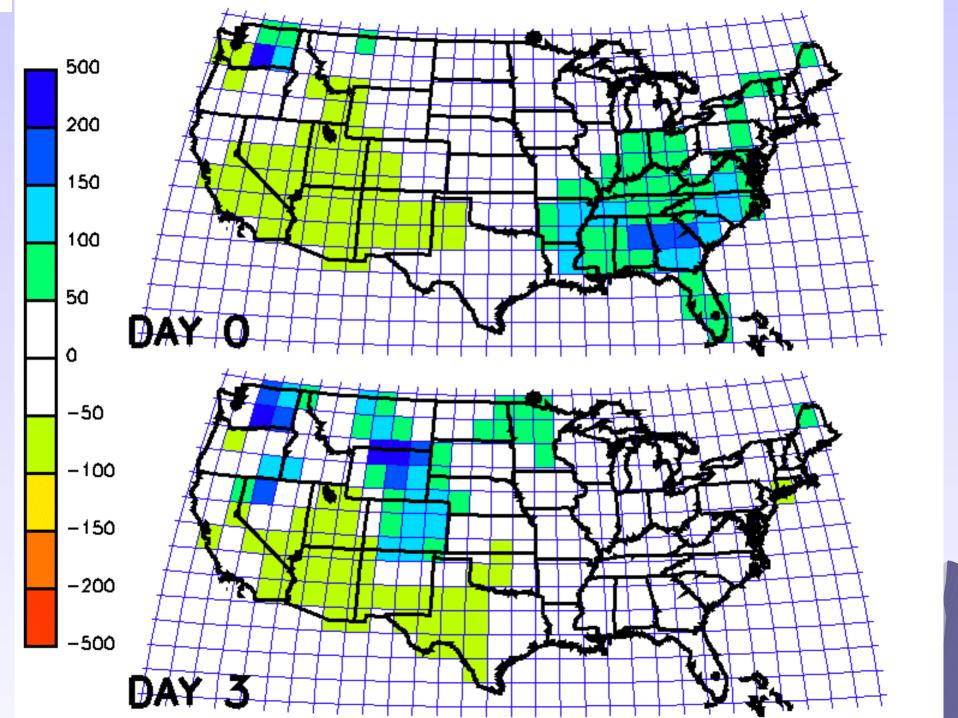
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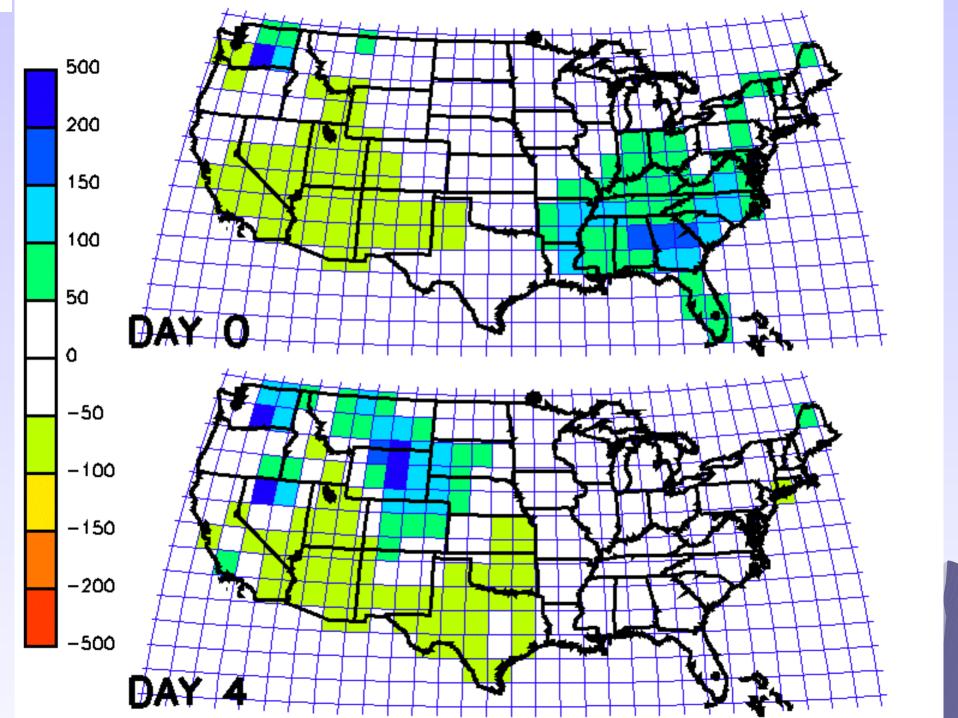


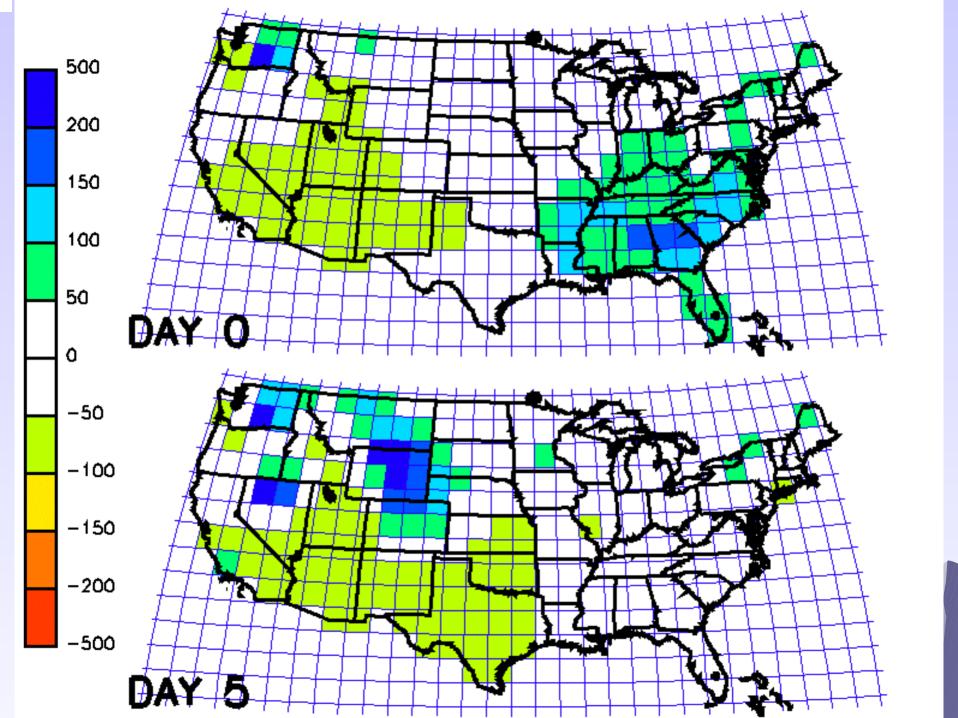
Precipitation biases are in excess of 100% of the mean

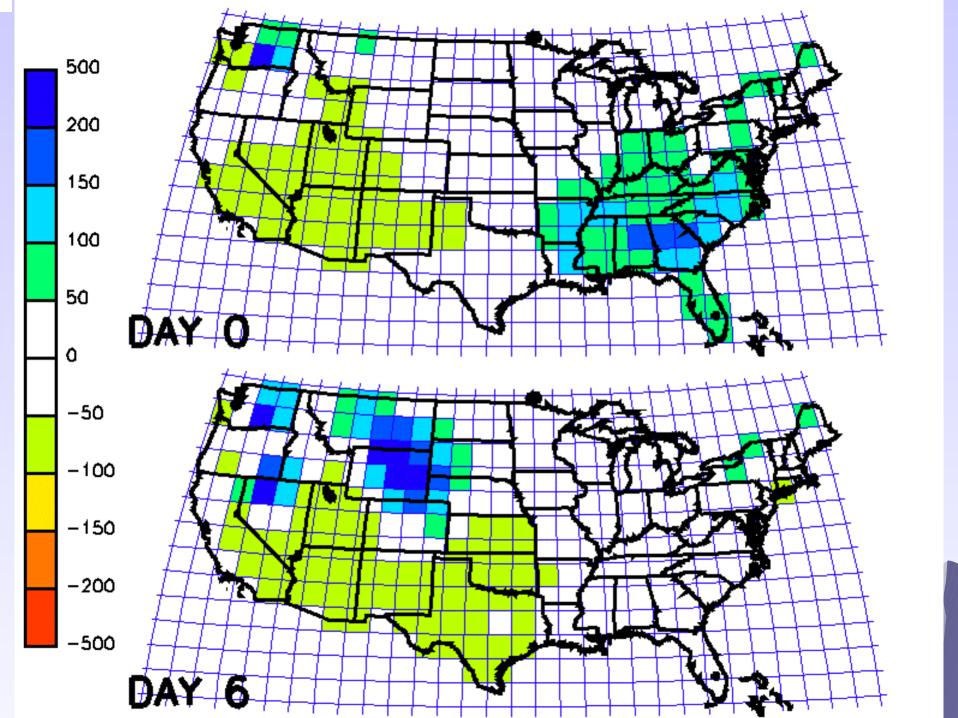


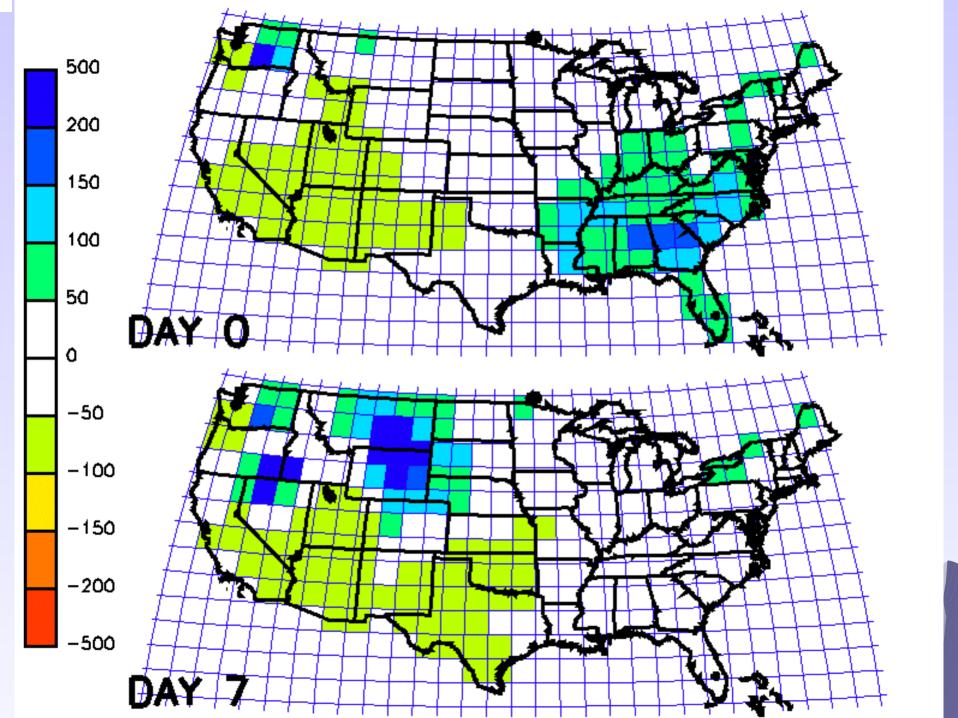


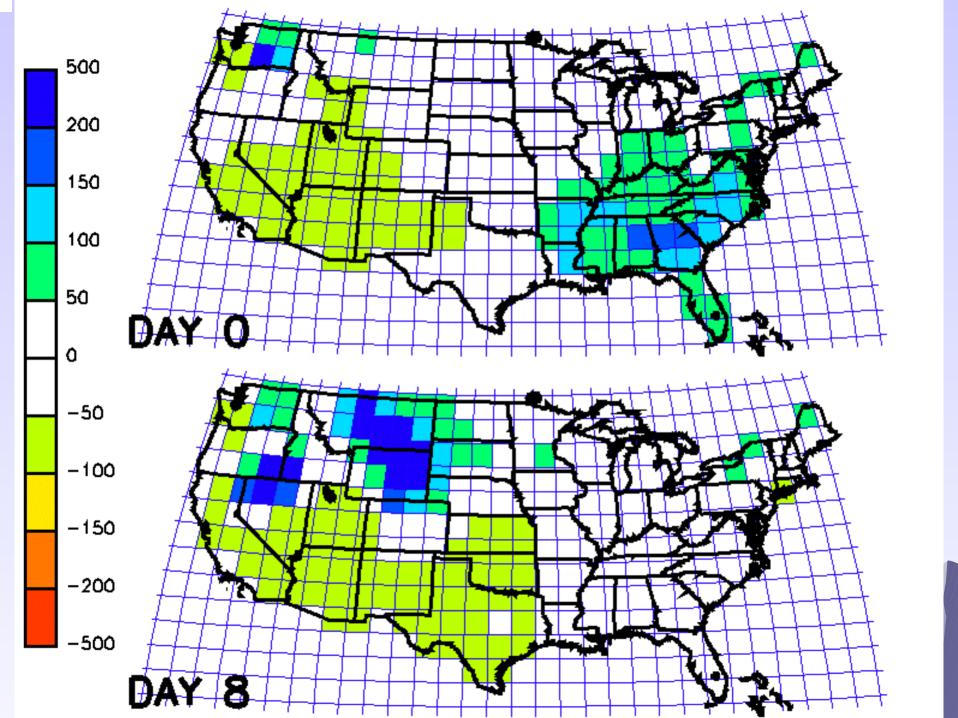




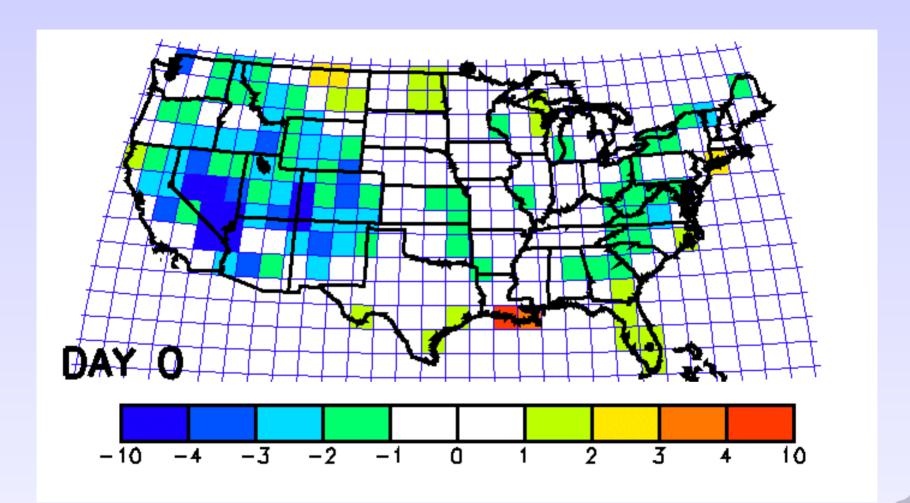






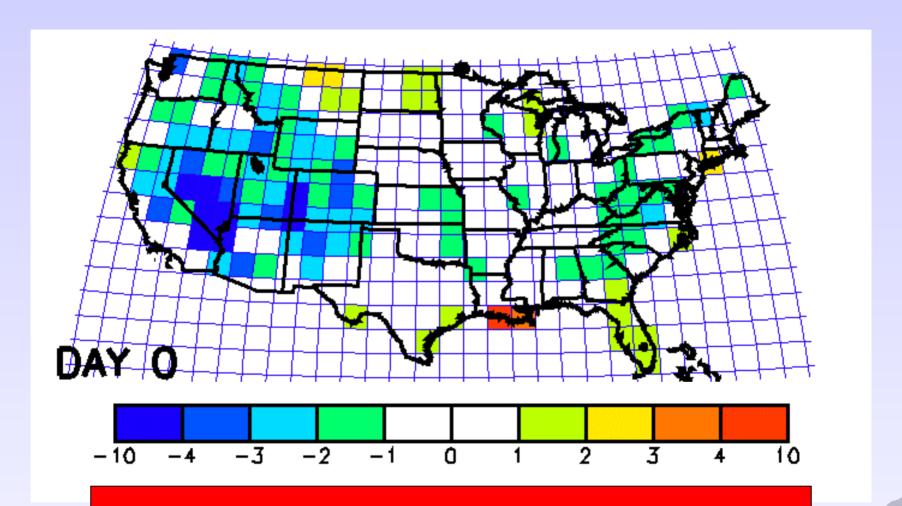


TEMPERATURE BIASES

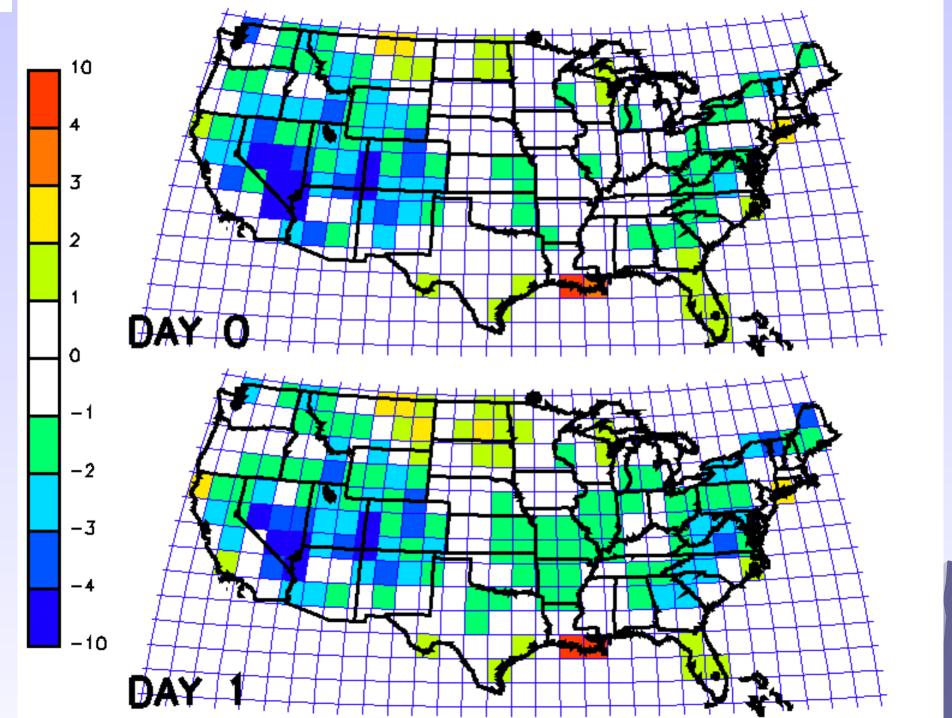


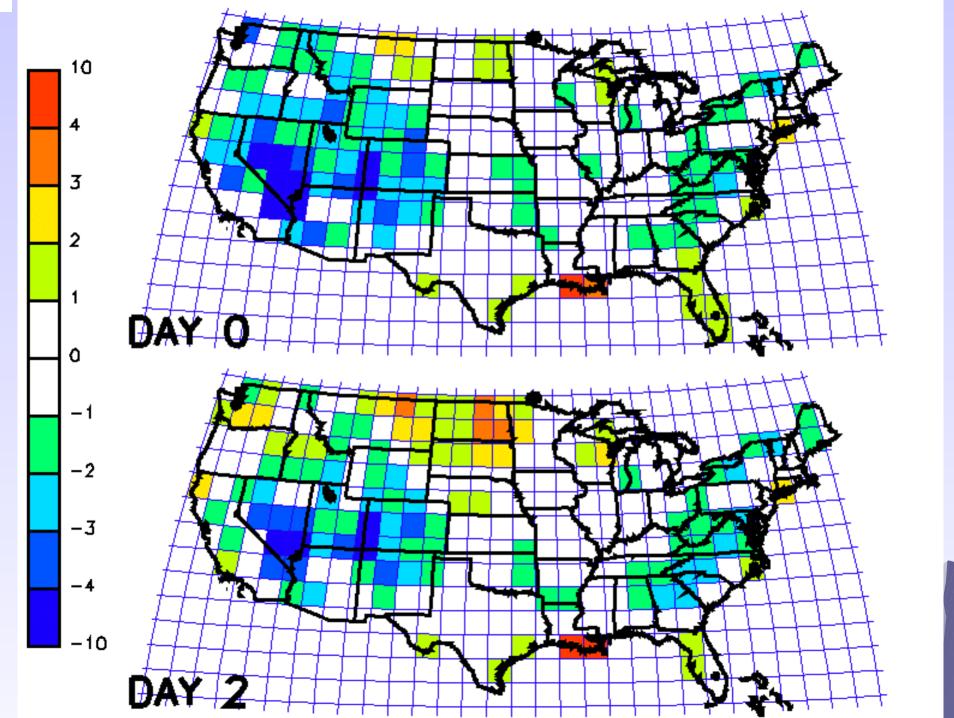
☐ Model January temperature biases (°C) in the NCEP/NCAR reanalysis

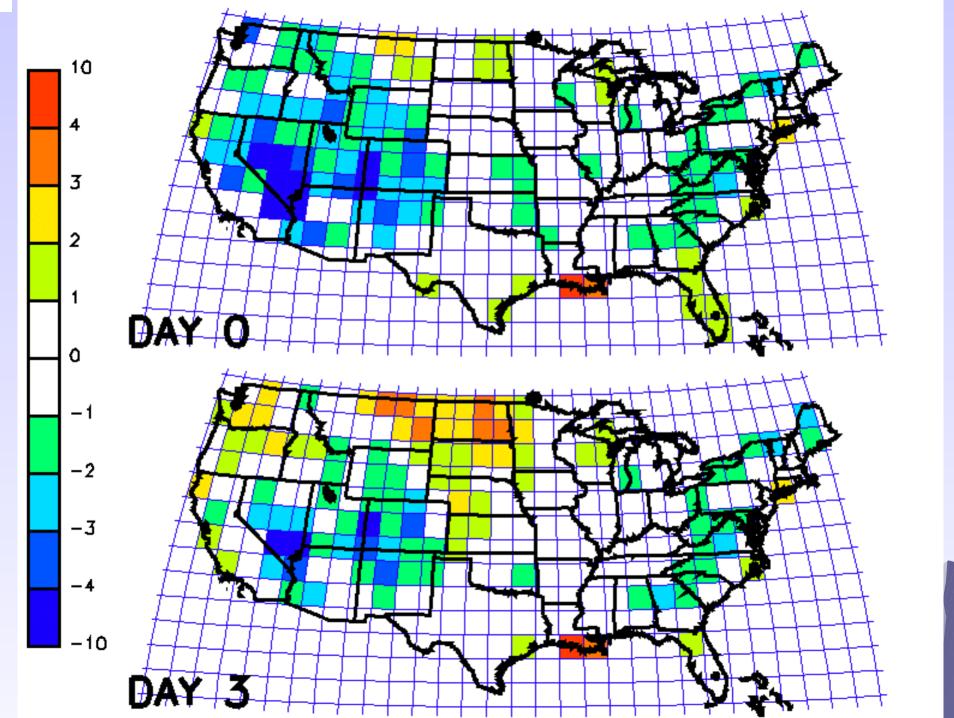
TEMPERATURE BIASES

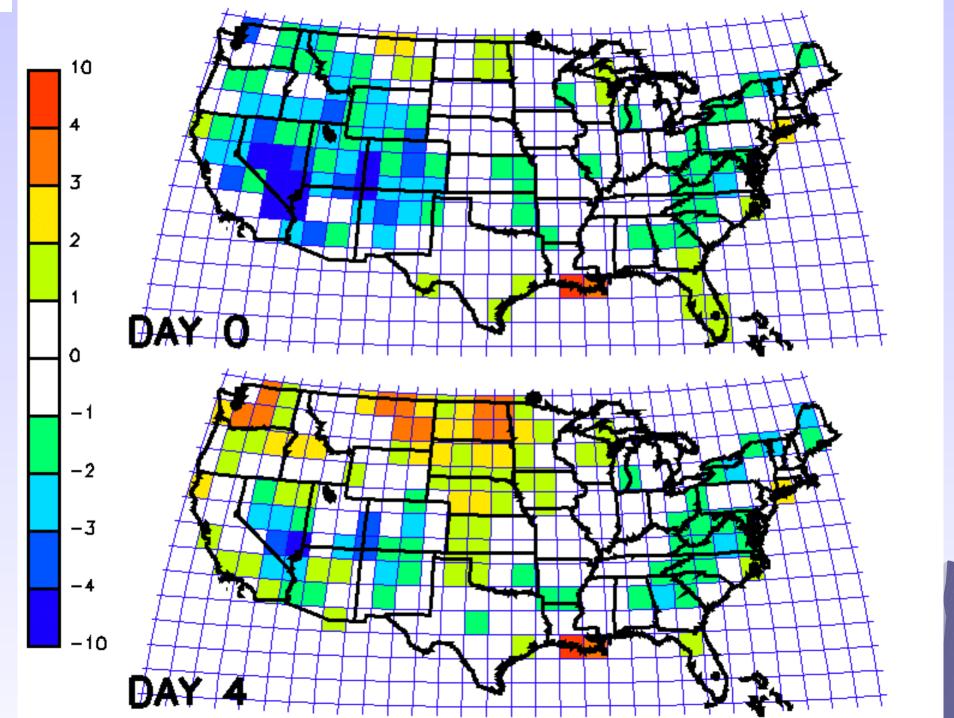


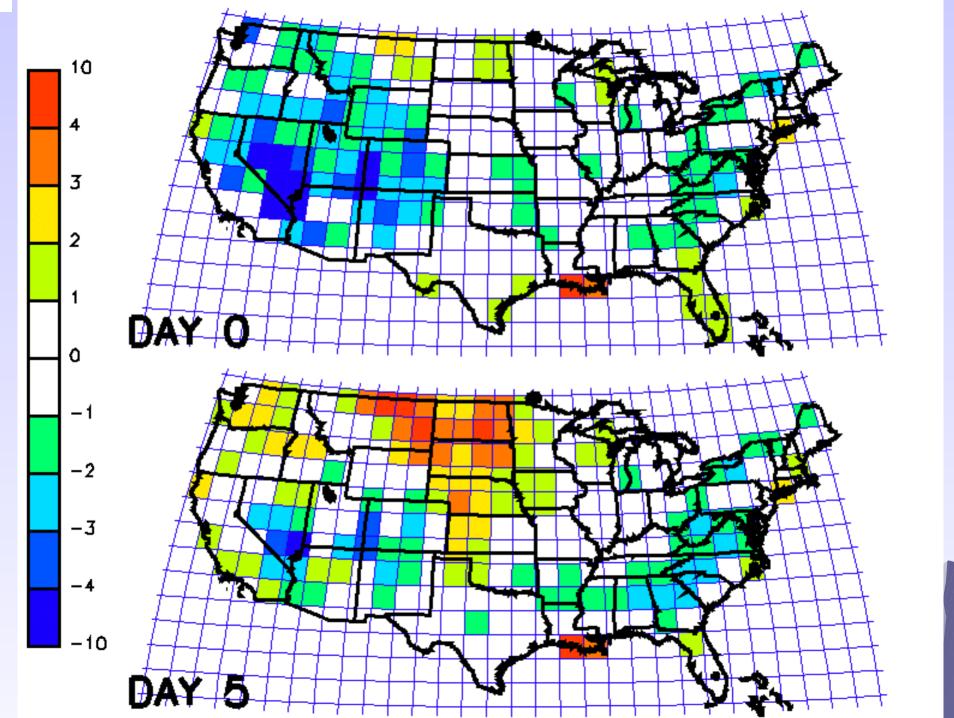
Temperature biases are in excess of 3°C

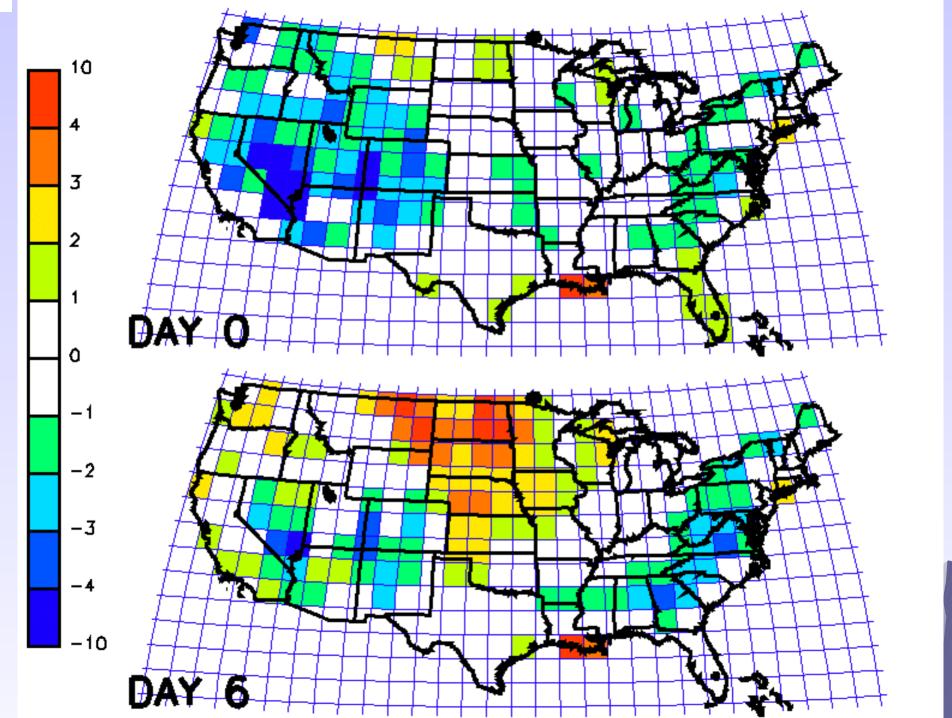


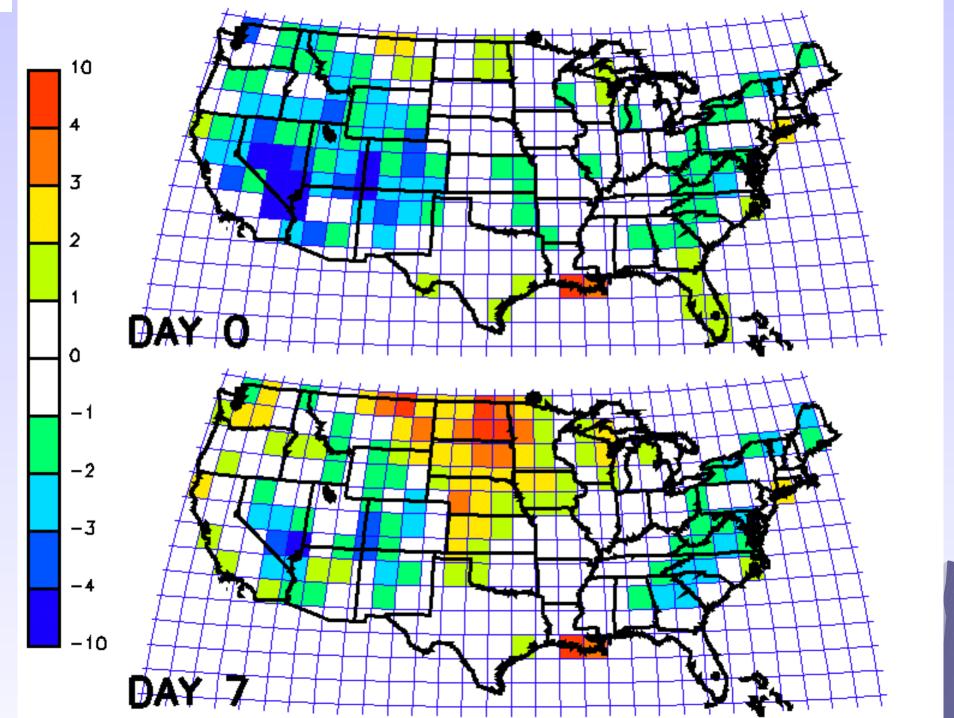


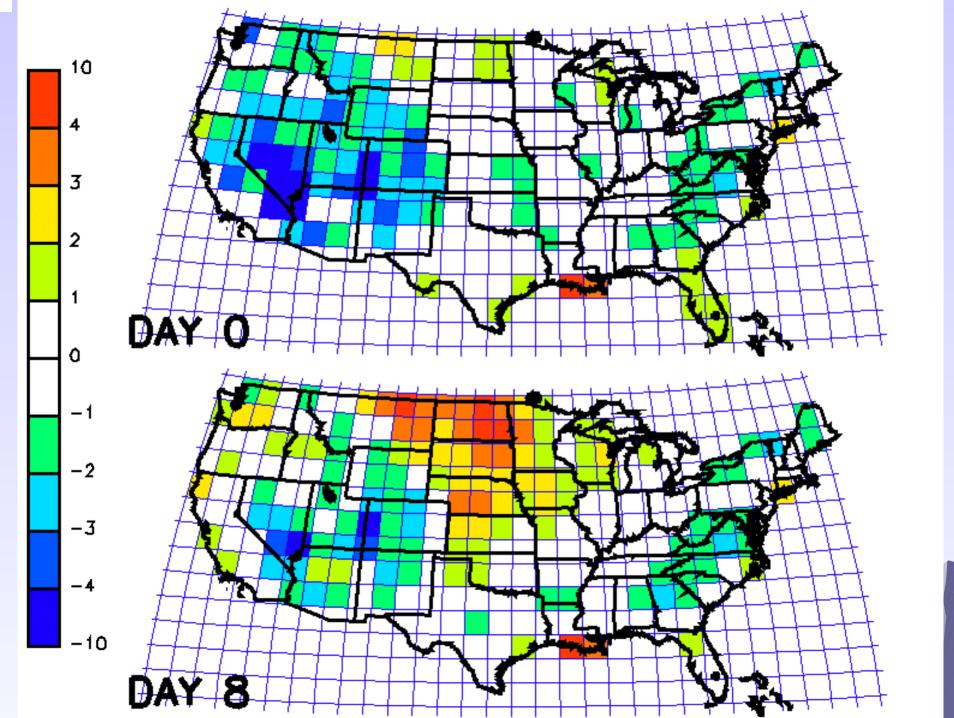


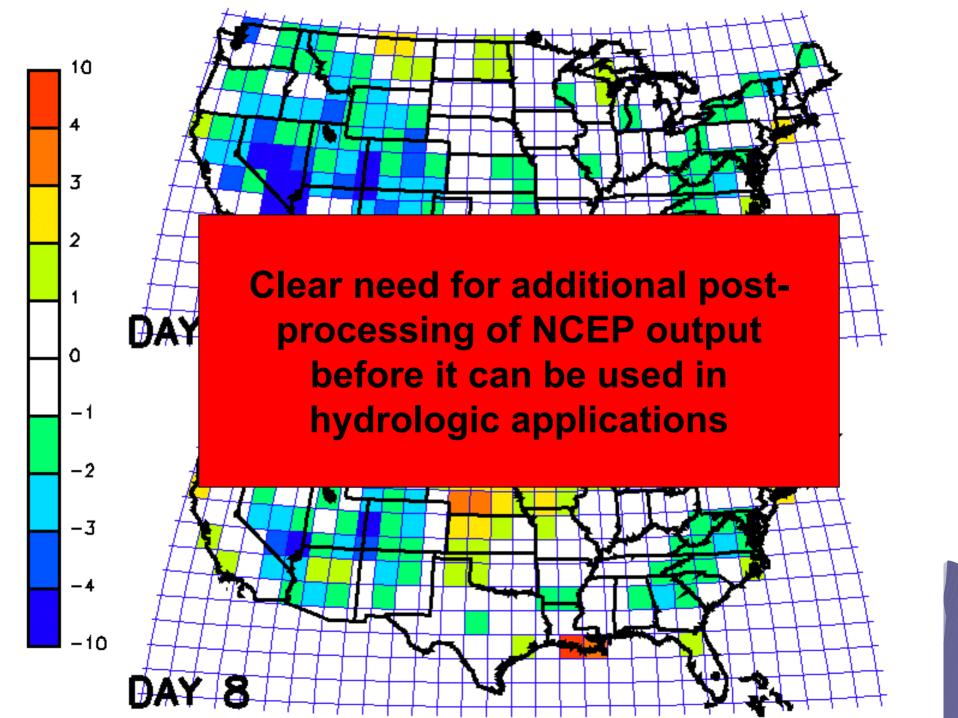












THE CDC-SCRIPPS RE-FORECAST EXPERIMENT

- □ Uses a fixed version (circa 1998) of the NCEP operational MRF.
- □ Ultimate goal to generate an ensemble of eleven 21-day forecasts for the past 23 years (1978-2001), initialized with boundary conditions from the reanalysis project
- □ Control run already completed.

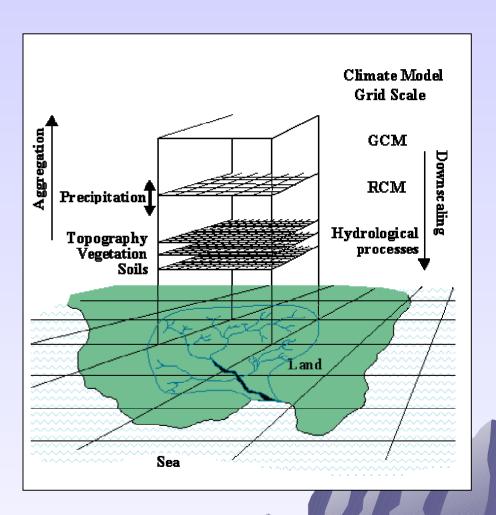
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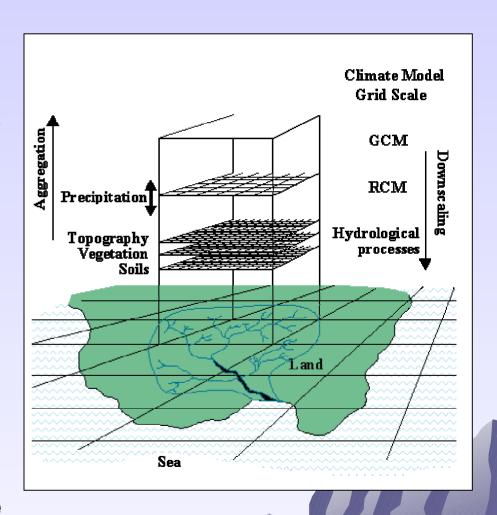
DOWNSCALING OF THE NCEP MRF OUTPUT

- □ Use Multiple linear Regression with forward selection
- □ Predictor Variables (over 300):
 - Geo-potential height, wind, and humidity at five pressure levels
 - Various surface flux variables
 - Computed variables such as vorticity advection, stability indices, etc.
 - Variables lagged to account for temporal phase errors in atmospheric forecasts.
- Predictands are maximum and minimum temperature, precipitation occurrence, and precipitation amounts



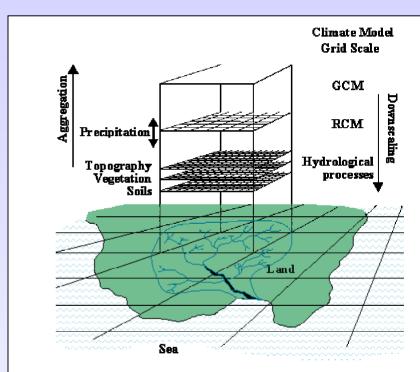
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- Use cross-validation procedures for variable selection – typically less than 8 variables are selected for a given equation
- Stochastic modeling of the residuals in the regression equation to provide ensemble time series



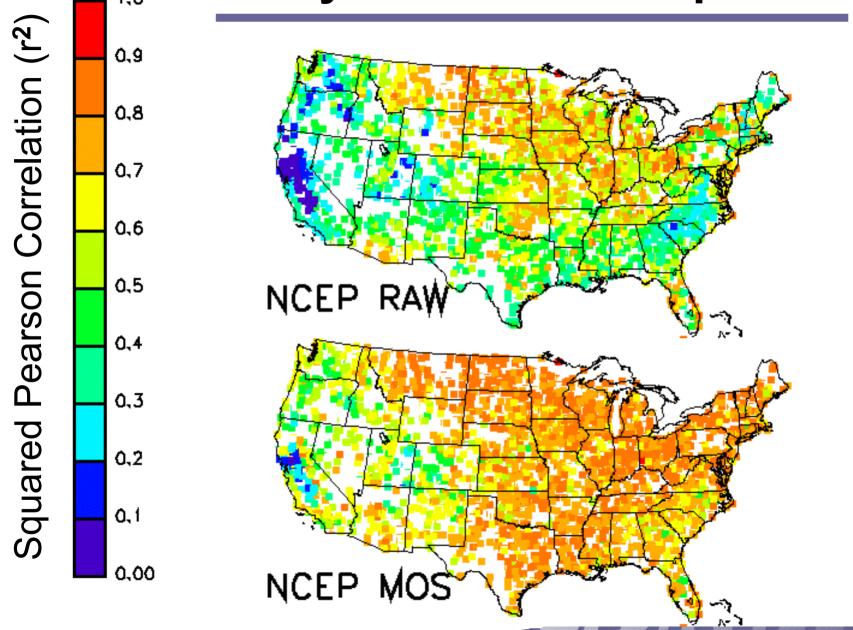
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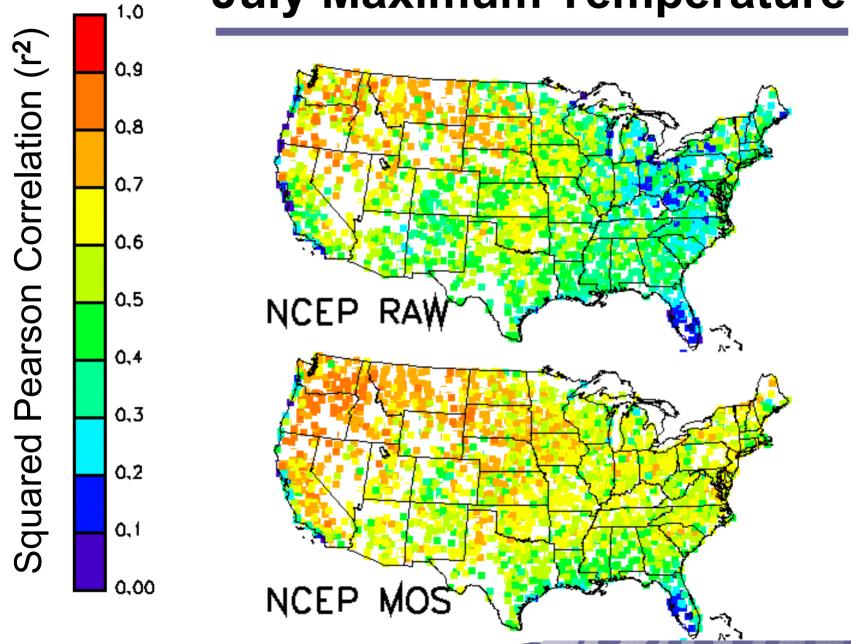


- •A separate equation is developed for each station, each forecast day, and each month.
- Equations developed over the period 1958-1976, and validated for the period 1977-1998.

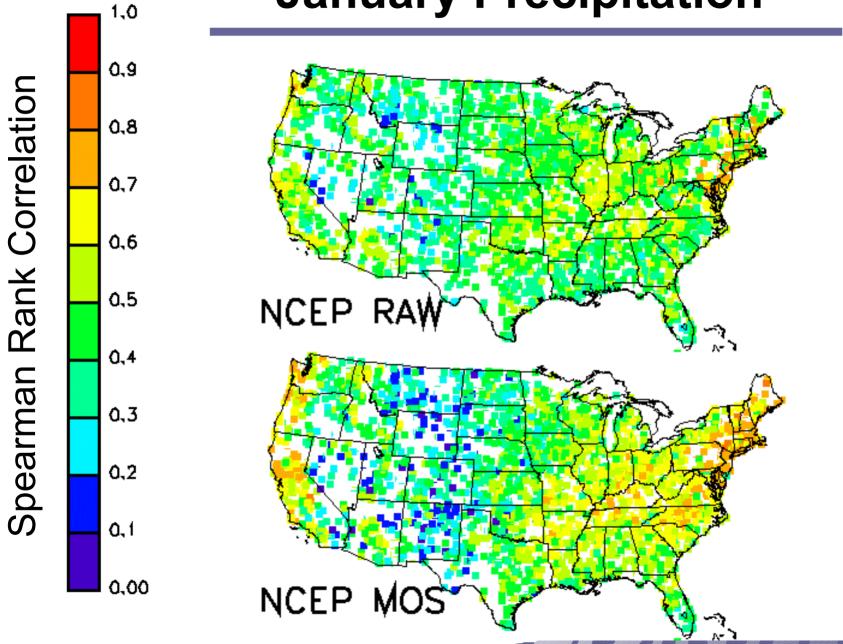
_{1,0} January Maximum Temperature



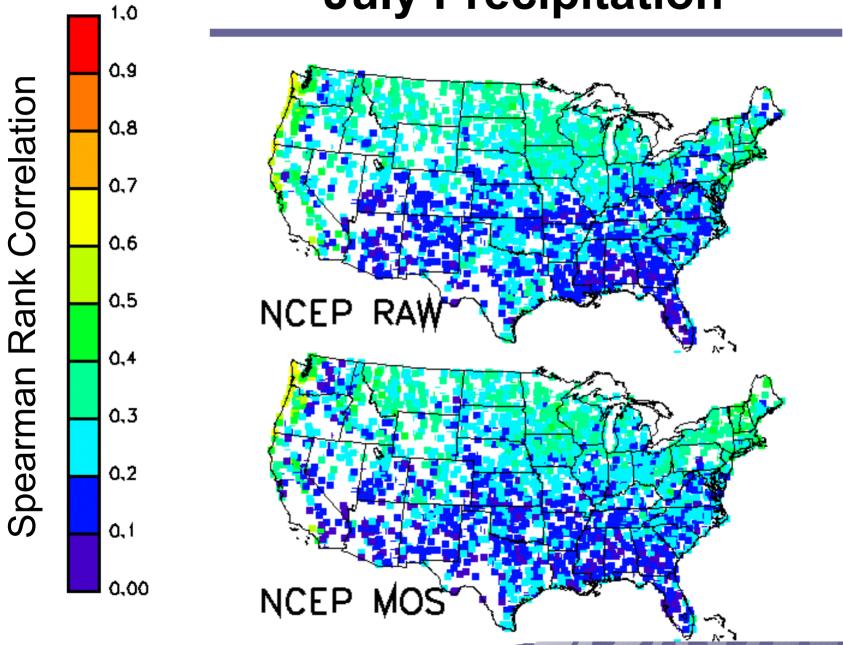
July Maximum Temperature



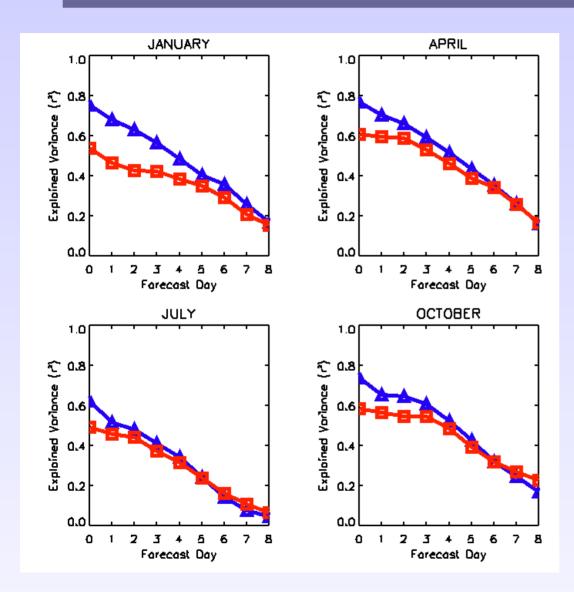
January Precipitation



July Precipitation



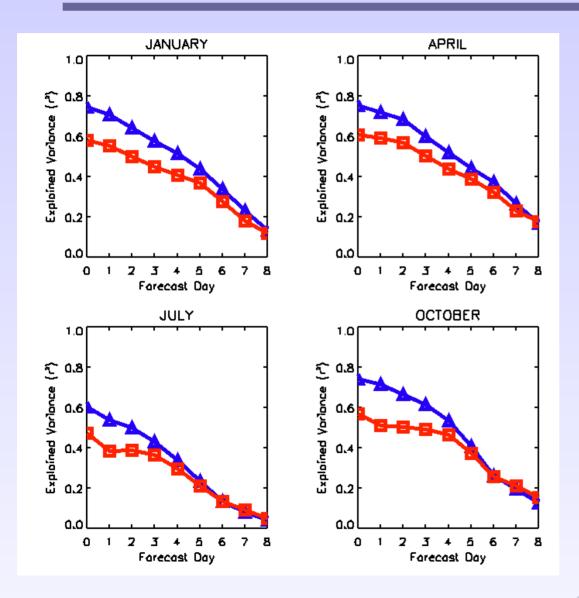
SKILL OF MAXIMUM TEMPERATURE PREDICTIONS



□ Median explained variance of maximum temperature predictions, computed for the 11,000 NWS co-op stations.
 □ Red is raw NCEP predictions, blue is based

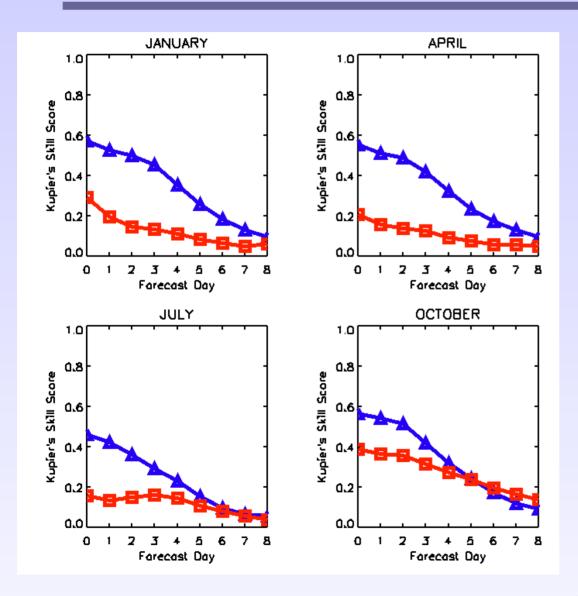
on MOS guidance.

SKILL OF MINIMUM TEMPERATURE PREDICTIONS



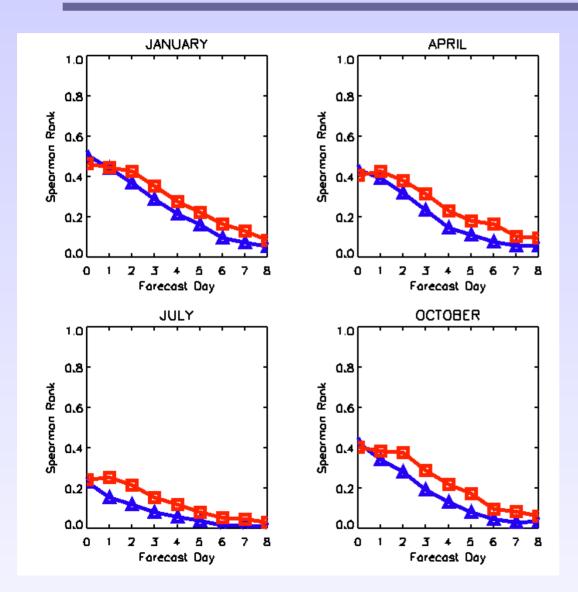
□ Median explained variance of minimum temperature predictions, computed for the 11,000 NWS co-op stations.
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SKILL OF PRECIP OCCURRENCE PREDICTIONS



□ Median explained variance of precipitation occurrence predictions, computed for the 11,000 NWS co-op stations.
 □ Red is raw NCEP predictions, blue is based on MOS guidance.

SKILL OF PRECIPITATION PREDICTIONS



- ☐ Median explained variance of precipitation predictions, computed for the 11,000 NWS co-op stations.
- ☐ Red is raw NCEP predictions, blue is based on MOS guidance.

INTRASEASONAL HYDROLOGIC FORECASTS

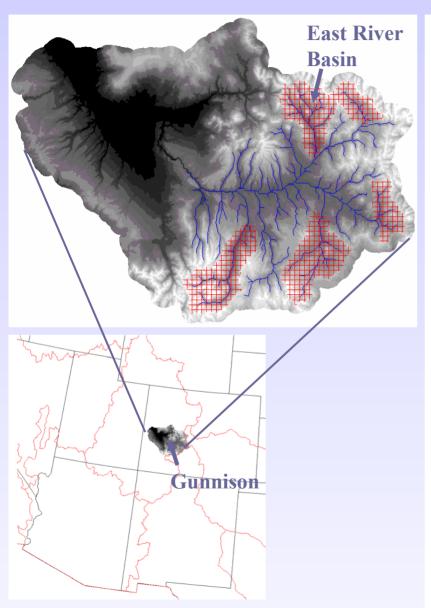
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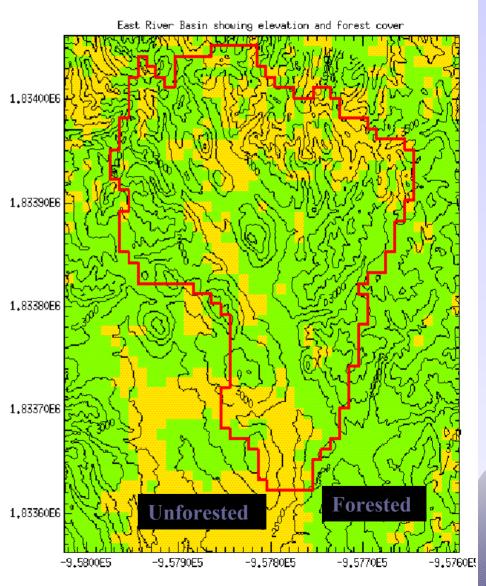
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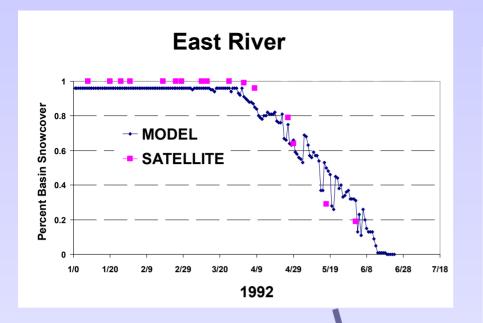
Estimate basin initial conditions

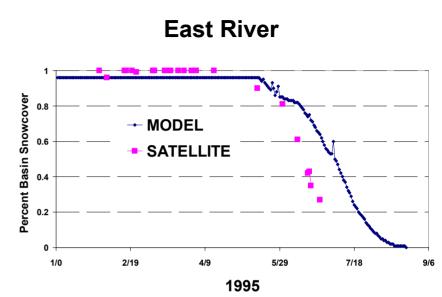


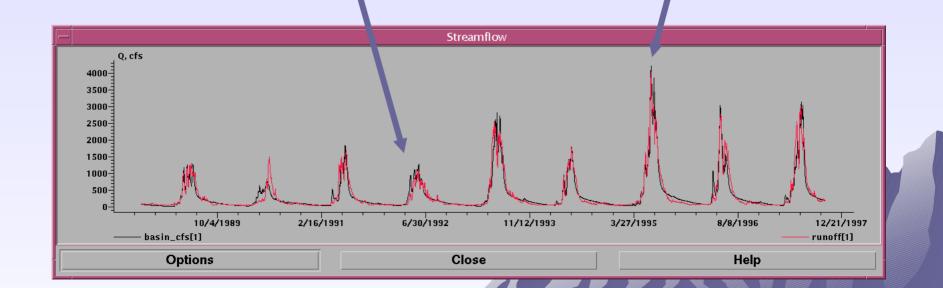
INITIAL STUDY AREA



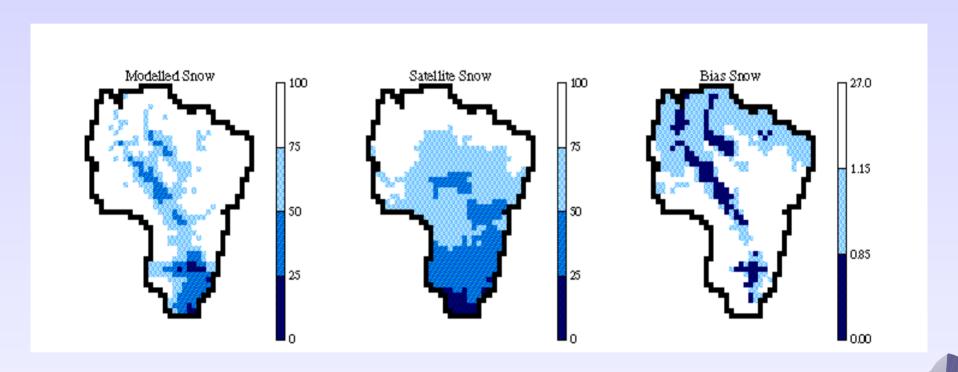




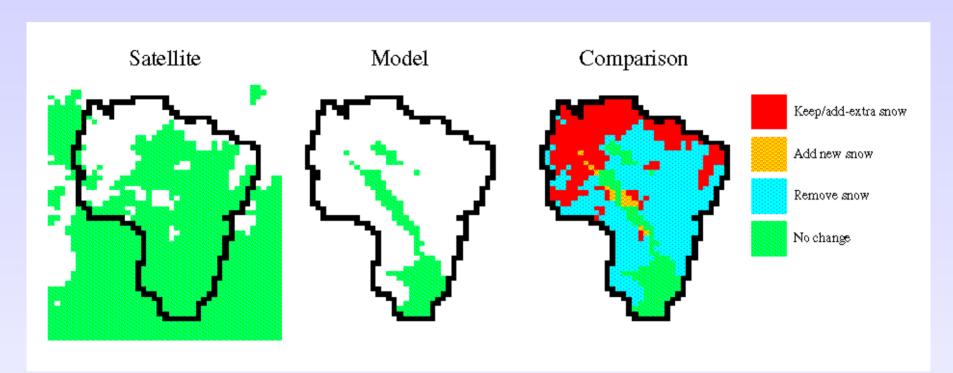




AVERAGE SPATIAL DISTRIBUTION OF SNOW COVER AND BIAS



COMPARISON OF SATELLITE- AND MODEL-DERIVED SNOW COVER MAPS



NOHRSC satellite-derived and model snow maps for 2 June 1997, and the results of a comparison of these maps.

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MULTI-MODEL SUPER-ENSEMBLES IN HYDROLOGY

Two Hypotheses:

- □The mean of runoff simulations from multiple models will be superior to the runoff simulation from any given model
- □The spread of the hydrologic model ensemble is related to the error in the hydrologic simulation

SUMMARY AND OUTLOOK

- □ The large biases in output from medium range forecast models creates a need for post-processing of model output in order for it to be effectively used in hydrologic simulations.
- Our downscaling system is successful in both removing mean model biases, and improving the skill in the raw NCEP output.
- □ When the downscaled NCEP output is used as input to hydrologic models, forecasts of runoff have greater skill than the forecasts generated with the traditional ESP approach.